공학석사학위논문

# 확장칼만필터를 이용한 EGR이 적용된 가솔린 엔진의 공기 흡입량 예측

**Intake Air Mass Flow Estimation of EGR Equipped SI Engine Using Centralized and Decentralized EKF**

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# Abstract

# Intake Air Mass Flow Estimation of EGR Equipped SI Engine Using Centralized and Decentralized EKF

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In order to reduce vehicle emission, Three Way Catalyst (TWC) is the key component of Spark Ignition (SI) engine. Since TWC has maximum efficiency point around stoichiometric Air Fuel Ratio (AFR) of mixture gas, AFR should be controlled precisely in the neighborhood of stoichiometric ratio. In order to control it precisely, accurate air mass flow estimation is necessarily required. Air mass flow estimation can be calculated using intake manifold pressure and volumetric efficiency which is derived by experiment. Even though pressure sensor in intake manifold is available, however, it can be inaccurate

in rapidly changing transients because sensor has its own delay. That is, manifold pressure needs to be modeled to estimate accurate air mass flow rate to intake valve.

In this study, Extended Kalman Filter (EKF) is used to estimate intake manifold pressure. For model prediction of EKF it is used that dynamics of intake manifold pressure changes by throttle, EGR, intake valve flow, and pumping fluctuation. For observer update of EKF, intake manifold pressure sensor and air mass flow sensor are used. Since two types of sensor are available for observer update, centralized and decentralized form of EKF can be applied for estimation. Root Mean Square Error (RMSE) is calculated based on assumption that Engine Management System (EMS) value is true value.

**Keywords: Gasoline Engine, Intake Manifold, Air Mass Flow Estimation, Extended Kalman Filter**

**Student Number: 2018-27486**

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# Chapter 1

# Introduction

## 1.1. Background and motivation

Emission regulation becomes stricter to meet its standard. In other words, modern vehicles need to reduce more emission than before. For example, in order to meet Super Ultra-Low Emissions Vehicle 20 (SULEV 20) standard released by California Air Resources Board (CARB) in 2005, it needs to be NMOG+NOx under 0.020g/mi, CO under 1.0g/mi, PM under 0.01g/mi, and HCHO under 4mg/mi. It means SULEV 20 vehicle needs to produce 90% fewer emission than the previous average gasoline vehicle.

Three Way Catalyst (TWC) is the key component of Spark Ignition (SI) engine in order to reduce emission such as HC, NOx, and CO. Since TWC has maximum efficiency point around stoichiometric Air Fuel Ratio (AFR) of mixture gas, AFR should be controlled accurately. Therefore, this stoichiometric number is regarded as important number and it is commonly called lambda is one ($\lambda$=1). Conversion efficiency of each emission according to A/F is shown in Figure 1.

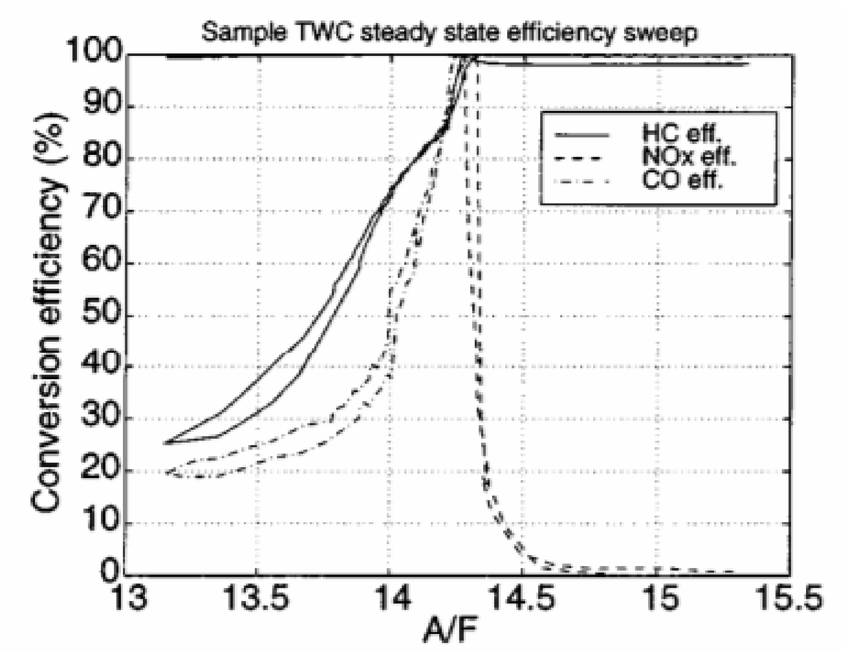


**Figure 1 TWC efficiency by A/F ratio**

In order to obtain accurate AFR, three accurate control are required: accurate air mass flow estimation through throttle valve, accurate air mass flow estimation through EGR valve, and accurate amount of fuel injection. If accurate estimations of air mass flow of throttle, EGR are possible, then amount of injection can be controlled by using oxygen sensor in exhaust manifold because it can sense $\lambda$ of air-fuel mixture. That is, It makes controller possible to stay $\lambda$ in the neighborhood one.

## 1.2. Objective of the study

Scheme of the intake manifold system of this paper is shown in Figure 2.

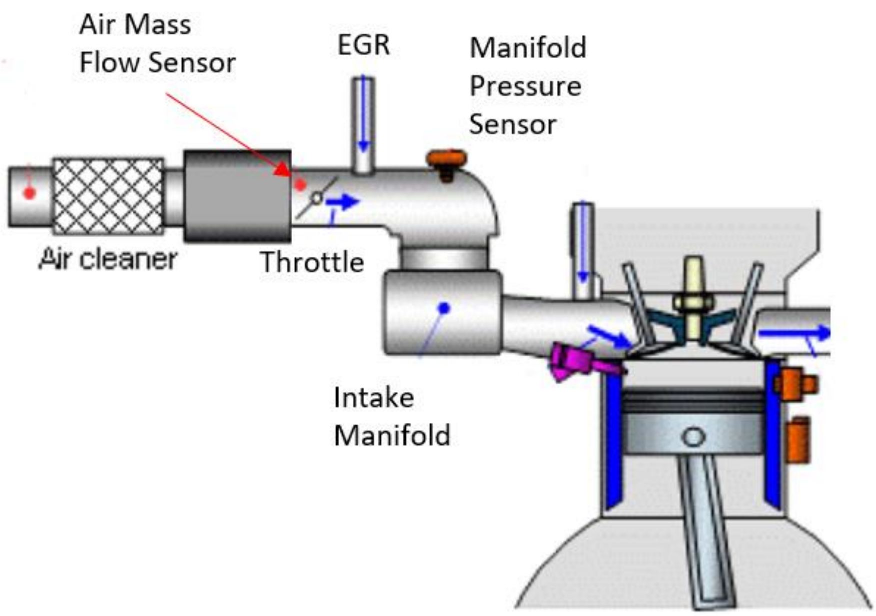


**Figure 2 Intake system with EGR**

The goal of this paper is to estimate precise air mass flow rate using two different type sensors – manifold pressure sensor, air mass flow sensor – and Extended Kalman Filter (EKF). Since this system has more than one sensor, two different form of EKF can be used – centralized EKF and decentralized EKF.

In this paper, intake manifold system is subject to following assumptions.

1. Flowing fluid is ideal gas. ($PV = mRT$)
2. Process is adiabatic ($PV^{\gamma} = \text{constant}$)
3. Process is isentropic ($dU = nC_v dT, dH = nC_p dT$)
4. Flow is inviscid (no shear stress or friction)

# Chapter 2

# Air Mass Flow Model

## 2.1. Throttle Flow Model

Throttle flow model use assumption that throttle flow is nozzle flow. Since nozzle flow has different characteristic depending on pressure ratio of downstream and upstream pressure, throttle flow model needs to be separated in three cases. [1]

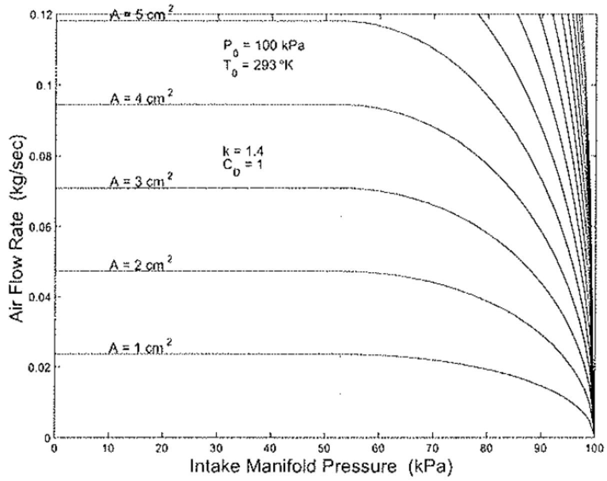


**Figure 3 Air mass flow rate by intake manifold pressure**

**Supersonic Flow**

Pressure ratio $\psi_{thr}$ is defined as the ratio of downstream pressure and upstream pressure of throttle $(\frac{p_m}{p_a})$. When $\psi_{thr}$ is under critical point $\psi_{crit}$, it is considered as supersonic flow and mass flow rate can be modeled as

$$\dot{m_{thr}} = \frac{P_{thr}A_{thr}}{\sqrt{RT_{thr}}}\sqrt{k\left(\frac{2}{k+1}\right)^{\frac{k+1}{k-1}}} \quad \text{if} \quad \psi_{thr} < \psi_{crit}$$

Where k=1.4, $\psi_{crit} = \left(\frac{2}{k+1}\right)^{\frac{k}{k-1}} = 0.5283$

**Subsonic Flow**

When pressure ratio $\psi_{thr}$ is above the critical point ($\psi_{crit}$), it is considered as subsonic flow, and mass flow rate can be modeled as

$$\dot{m_{thr}} = \frac{P_{tps}A_{tps}}{\sqrt{RT_{thr}}}\sqrt{\frac{2k}{k-1}\left[\psi_{thr}^{\frac{2}{k}} - \psi_{thr}^{\frac{k+1}{k}}\right]} \quad \text{if} \quad \psi_{crit} < \psi_{thr} < 0.97$$

**High pressure ratio**

Mass flow rate function has large gradient in high pressure ratio area. Due to this characteristic, small variation of pressure ratio can cause large variations in mass flow rate estimation. [2] In order to avoid inaccurate estimation, throttle mass flow rate is assumed to be equal to intake valve mass flow rate when $\psi_{thr} > 0.97$.

$$\dot{m}_{thr} = \dot{m}_{inv} \text{ if } 0.97 < \psi_{thr}$$

## 2.2. EGR Flow Model

Since Exhaust Gas Recirculation (EGR) has same butterfly valve as throttle valve, same model used as throttle flow model.

**Supersonic flow**

When $\psi_{egrv}$ is under critical point ($\psi_{crit}$), it is considered as supersonic flow and it can be modeled as

$$\dot{m}_{egrv} = \frac{P_{egrv}A_{egrv}}{\sqrt{RT_{egrv}}}\sqrt{k\left(\frac{2}{k+1}\right)^{\frac{k+1}{k-1}}} \text{ if } \psi_{egrv} < \psi_{crit}$$

Where k=1.4, $\psi_{crit} = \left(\frac{2}{k+1}\right)^{\frac{k}{k-1}} = 0.5283$

**Subsonic flow.**

Pressure ratio $\psi_{egrv}$ is defined as the ratio of downstream pressure and upstream pressure of EGR valve ($\frac{p_m}{p_{egrv}}$). When pressure ratio $\psi_{egrv}$ is above the critical point $\psi_{crit}$, it is considered as subsonic flow, and mass flow can be modeled as

$$\dot{m}_{egrv} = \frac{P_{egrv}A_{egrv}}{\sqrt{RT_{egrv}}}\sqrt{\frac{2k}{k-1}\left[\psi_{egrv}^{\frac{2}{k}} - \psi_{egrv}^{\frac{k+1}{k}}\right]} \text{ if } \psi_{crit} < \psi_{egrv}$$

## 2.3. Intake Valve Flow Model

Establishing model of mass flow rate to intake valve is difficult because multi variables need to be considered such as RPM, Variable Valve Timing (VVT), Variable Valve Lifting (VVL), etc. Since its complexity of calculation, volumetric efficiency $\eta$ is conventionally used for modeling of intake valve mass flow rate. $\eta$ is highly nonlinear function which is usually attained by engine dynamometer test. It is graphically described in Figure 4.

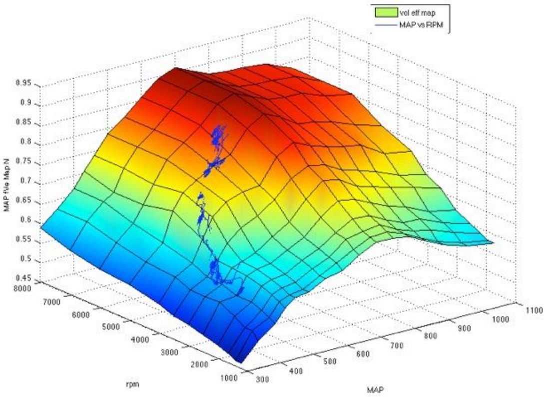


**Figure 4 Volumetric efficiency**

It is obtained at several steady state engine operating point and calculated for other point by interpolation. Intake valve air mass flow rate is modeled as

$$\dot{m}_{inv} = \eta_{slop} \times p_m - \eta_{ofs}$$

## 2.4. Intake Manifold Pressure Model

Since change of air mass of manifold is equal to sum of all air mass flow, manifold model is defined as

$$\frac{dm_m}{dt} = \dot{m}_{thr} + \dot{m}_{egrv} - \dot{m}_{inv} \qquad (1)$$

Ideal gas low equation is defined as

$$m_m = \frac{P_m V_m}{RT_m}$$

Since $V_m, R, T_m$, do not change in time, we can take derivative

$$\dot{m}_m = \frac{V_m}{RT_m}\dot{P}_m \qquad (2)$$

Using equation (1), (2), we can establish intake manifold pressure model as

$$\dot{P}_m = \frac{RT_m}{V_m}(\dot{m}_{thr} + \dot{m}_{egrv} - \dot{m}_{inv})$$

## 2.5. Pumping Fluctuation

As intake valves open and close it affects manifold pressure periodically. [3] Figure 5 shows the intake manifold pressure changes of idle engine by pumping fluctuation.

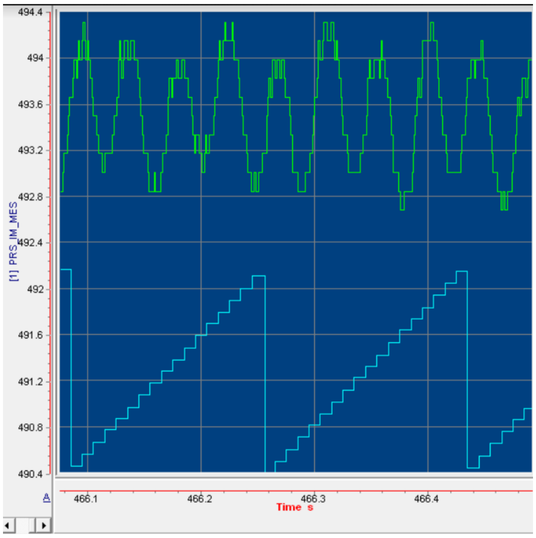


**Figure 5 Manifold pressure changes by pumping fluctuation**

This periodical pressure changes can be modeled by 2nd order equation

$$\ddot{q} + 2\xi\omega\dot{q} + \omega^2 q = 0$$

Where q is pressure changes by pumping fluctuation. $\omega$ can be described as $\omega = 2\pi f = 2\pi\frac{N}{30}$ where N is engine RPM since pumping fluctuation appears two times in every crankshaft rotation

## 2.6. Sensor Model

Intake manifold pressure sensor has first order low pass filter characteristic and it measures intake manifold pressure after changes by pumping fluctuation.

$$\dot{p}_{mes} = -\frac{1}{\tau_{map}} p_{mes} + \frac{1}{\tau_{map}} (p_m + q)$$

Air mass flow sensor has also first order low pass filter characteristic

$$\dot{m}_{mes} = \frac{1}{\tau_{maf}} \dot{m}_{mes} + \frac{1}{\tau_{maf}} \dot{m}_{thr}$$

# Chapter 3

# Intake Air Mass Flow Observer

## 3.1. Discrete Plant model

In order to implement simulation, all models need to be discretized.

**Sampling time**

Current Engine Management System (EMS) uses calculation values related to intake manifold model with segment-based recurrence, which means it is updated four times in every crankshaft rotation. Therefore, sampling time needs to be set

$$\Delta t = \frac{180}{6N}$$

Where N is rpm.

**Intake manifold model**

Recall that intake valve model in time domain is

$$\dot{P_m} = \frac{V_m}{RT_m}(\dot{m_{thr}} + \dot{m_{egrv}} - \dot{m_{inv}})$$

It is discretized by first-order Euler method

$$P_m(k+1) = P_m + \Delta t \frac{V_m}{RT_m}(\dot{m_{thr}} + \dot{m_{egrv}} - \dot{m_{inv}})$$

Since $\dot{m_{thr}}$, $\dot{m_{egr}}$ are modeled different by its pressure ratio, it needs to be divided to 6 models for simulation.

**Pumping fluctuation**

Recall that pumping fluctuation model in time domain is

$$\ddot{q} + 2\xi w\dot{q} + w^2 q = 0$$

Where $w = 2\pi f = 2\pi\frac{N}{30}$.

Let $q_1 = q, q_2 = \dot{q_1}$, then

$$\begin{bmatrix}\dot{q_1}\\ \dot{q_2}\end{bmatrix} = \begin{bmatrix}0 & 1\\ -w^2 & -2\xi w\end{bmatrix}\begin{bmatrix}q_1\\ q_2\end{bmatrix}$$

Let $A = \begin{bmatrix}0 & 1\\ -w^2 & -2\xi w\end{bmatrix}$, then $q_1, q_2$ can be discretized as

$$\begin{bmatrix}q_1(k+1)\\ q_2(k+1)\end{bmatrix} = e^{A\Delta t}\begin{bmatrix}q_1(k)\\ q_2(k)\end{bmatrix}$$

**Sensor model**

Recall that pressure sensor model in time domain is

$$\dot{p_{mes}} = -\frac{1}{\tau_{map}} p_{mes} + \frac{1}{\tau_{map}}(p_m + q)$$

It can be discretized as

$$\begin{aligned} P_{mes}(k+1) &= P_{mes}(k) + \Delta t \dot{P_{mes}}(k) \\ &= a_{map} p_{mes}(k) + \left(1 - a_{map}\right)\{P_m(k) + q_1(k)\} \end{aligned}$$

Where $a_{map} = \left(1 + \frac{\Delta t}{\tau_{map}}\right)^{-1}$

Likewise, air mass flow sensor model in time domain can be discretized as:

$$\dot{m}_{mes}(k+1) = a_{maf}\dot{m}_{mes}(k) + (1 - a_{maf})\dot{m}_{thr}$$

Where $a_{maf} = \left(1 + \frac{\Delta t}{\tau_{maf}}\right)^{-1}$

**State variable**

Let $\mathbf{x} = [p_m \ \ p_{mes} \ \ \dot{m}_{thr} \ \ \dot{m}_{mes} \ \ q_1 \ \ q_2]^T$, then we can obtain

$$\mathbf{x}(k+1) = \begin{bmatrix} P_m + \Delta t \frac{V_m}{RT_m}(\dot{m}_{thr} + \dot{m}_{egrv} - \dot{m}_{inv}) \\ a_{map}p_{mes}(k) + (1 - a_{map})(P_m(k) + q_1(k)) \\ \dot{m}_{thr} \\ a_{maf}\dot{m}_{mes}(k) + (1 - a_{maf})\dot{m}_{thr} \\ e^{A\Delta t}\begin{bmatrix} q_1(k) \\ q_2(k) \end{bmatrix} \end{bmatrix}$$

## 3.2. Centralized Extended Kalman Filter

Diagram of the centralized EKF structure is shown in Figure 6.

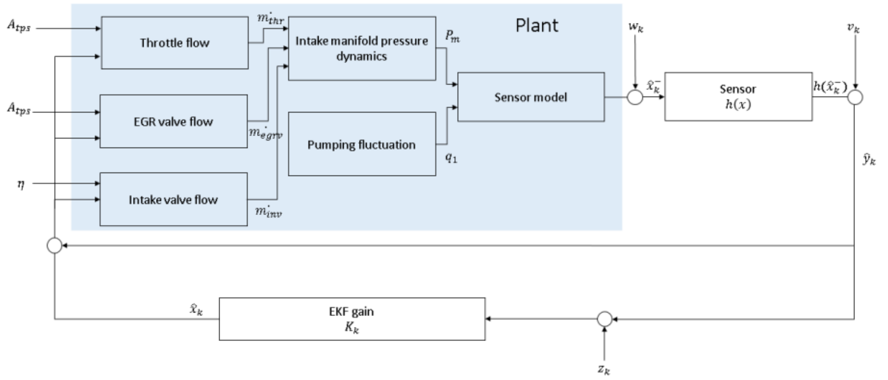


**Figure 6 Structure of centralized EKF**

Plant model can be described as below two equations.

$$x_{k+1} = f(x_k) + w_k$$

$$y_k = h(x_k) + \nu_k$$

Suppose that all noises are white Gaussian and not correlated. Therefore, following equations are satisfied.

$$w_k \sim N(0, Q_k)$$

$$\nu_k \sim N(0, R_k)$$

$$E\left[w_k w_{k+\tau}^T\right] = E\left[\nu_k \nu_{k+\tau}^T\right] = 0, \text{ for all } \tau$$

Let $\hat{x}(k-1|k-1)$ is estimated state vector after (k-1)th measurement update and $\hat{x}(k|k-1)$ is predicted state vector before kth measurement update, then following equations are satisfied

$$\hat{x}(k|k-1) = f\big(\hat{x}(k-1|k-1)\big)$$

$$\hat{y}_k = h\big(\hat{x}(k|k-1)\big)$$

Let $F_k, H_k$ be partial derivatives of f and h. (the Jacobian)

$$F_k = \frac{\partial f}{\partial x_k}, H_k = \frac{\partial h}{\partial x_k}$$

Let $P(k|k-1)$ is innovation covariance after (k-1)th measurement and $P(k|k)$ is updated covariance after kth measurement update, then covariance and state vector are updated as following equation.

$$P(k|k-1) = F_k P(k-1|k-1) F_k^T + Q_k$$

$$K_k = P(k|k-1) H_k^T \left(H_k P(k|k-1) H_k^T + R_k\right)^{-1}$$

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K_k (z_k - \hat{y}_k)$$

$$P(k|k) = P(k|k-1) - K_k \left(H_k P(k|k-1) H_k^T + R_k\right) K_k^T$$

$H_k = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$ is used for centralized EKF.

## 3.3. Decentralized Extended Kalman Filter

Diagram of the centralized EKF structure is shown in Figure 7.

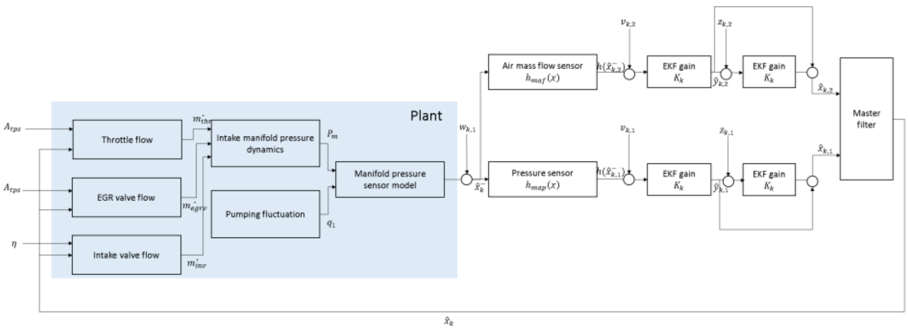


Figure 7 Structure of decentralized EKF

Plant model can be described as below three equations.

$$x_{k+1} = f(x_k) + w_k$$

$$y_{k,map} = h(x_k) + \nu_{k,map}$$

$$y_{k,maf} = h(x_k) + \nu_{k,maf}$$

Suppose that all noises are white Gaussian and not correlated. Therefore, following equations are satisfied.

$$W_k \sim N(0, Q_k)$$

$$\nu_{k,map} \sim N\left(0, R_{k,map}\right)$$

$$\nu_{k,maf} \sim N\left(0, R_{k,maf}\right)$$

$E\left[w_k w_{k+\tau}^T\right] = E\left[\nu_{k,map} \nu_{k,map+\tau}^T\right] = E\left[\nu_{k,maf} \nu_{k,maf+\tau}^T\right] = 0$, for all $\tau$.

Let $\hat{x}(k-1|k-1)$ is estimated vector after (k-1)th measurement update and $\hat{x}(k|k-1)$ is predicted state vector before kth measurement update, then following equations are satisfied

$$\hat{x}(k|k-1) = f\left(\hat{x}(k-1|k-1)\right)$$

$$\hat{y}_{k,map} = h_{map}\left(\hat{x}(k|k-1)\right)$$

$$\hat{y}_{k,maf} = h_{maf}\left(\hat{x}(k|k-1)\right)$$

Let $F_k, H_{k,map}, H_{k,maf}$ be partial derivatives of $f, h_{map}, h_{maf}$ to $x_k$. (the Jacobian)

$$F_k = \frac{\partial f}{\partial x_k}, H_{k.map} = \frac{\partial h_{map}}{\partial x_k}, H_{k.maf} = \frac{\partial h_{maf}}{\partial x_k}$$

Let $P(k|k-1)$ be innovation covariance after (k-1)th measurement and $P(k|k)$ is updated covariance after kth measurement update, then covariance and state vector are updated as following equation.

$$P(k|k-1) = F_k P(k-1|k-1) F_k^T + Q_k$$

$$K_{k,map} = P(k|k-1) H_{k,map}^T \left( H_{k,map} P(k|k-1) H_{k,map}^T + R_{k,map} \right)^{-1}$$

$$K_{k,maf} = P(k|k-1) H_{k,maf}^T \left( H_{k,maf} P(k|k-1) H_{k,maf}^T + R_{k,maf} \right)^{-1}$$

$$\hat{x}_{map}(k|k) = \hat{x}_{map}(k|k-1) + K_{k,map}(z_{k,map} - \hat{y}_{k,map})$$

$$\hat{x}_{maf}(k|k) = \hat{x}_{maf}(k|k-1) + K_{k,maf}(z_{k,maf} - \hat{y}_{k,maf})$$

$H_{k,map} = [0\ \ 1\ \ 0\ \ 0\ \ 0\ \ 0], H_{k,maf} = [0\ \ 0\ \ 0\ \ 1\ \ 0\ \ 0]$ are used for each decentralized EKF.

Covariance and state vector of master filter are updated as following equations. [4]

$$P_{k,m}^{-1} = P_{k,map}^{-1} + P_{k,maf}^{-1}$$

$$P_{k,m}^{-1} \hat{x}_{k,m} = P_{k,map}^{-1} \hat{x}_{k,map} + P_{k,maf}^{-1} \hat{x}_{k,maf}$$

# Chapter 4

# Simulation Results

## 4.1. Centralized Extended Kalman Filter

In order to estimate intake manifold pressure and air mass flow rate to intake valve, simulation needs basic data from EMS such as intake manifold temperature, throttle and EGR effective area, volumetric efficiency, etc. In order to obtain those basic data, test is executed with test vehicle of 4-cylinder 2.0 gasoline engine.

Simulation result of centralized EKF estimated intake manifold pressure is shown in Figure 8, 9 with pressure sensor value, pressure value from EMS.

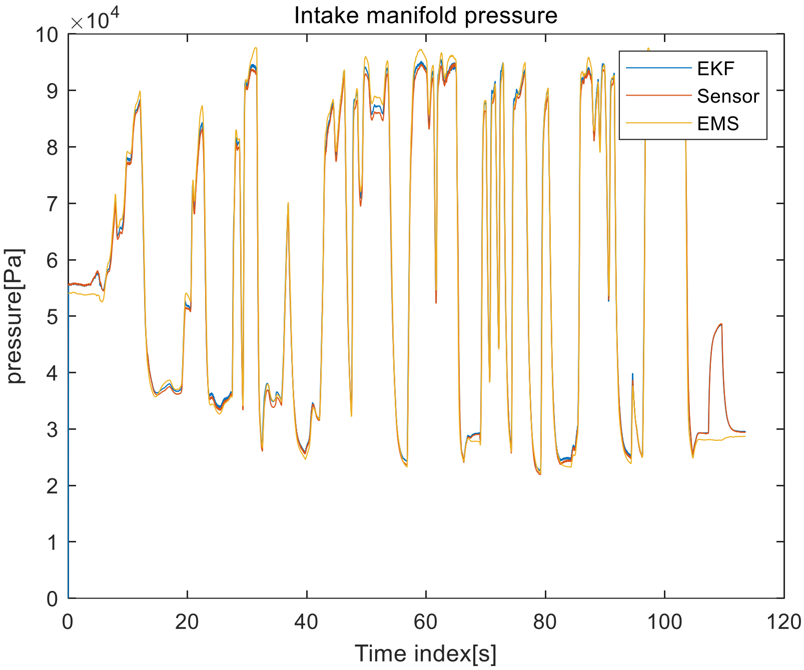


**Figure 8 Estimated intake manifold pressure of centralized EKF (1)**

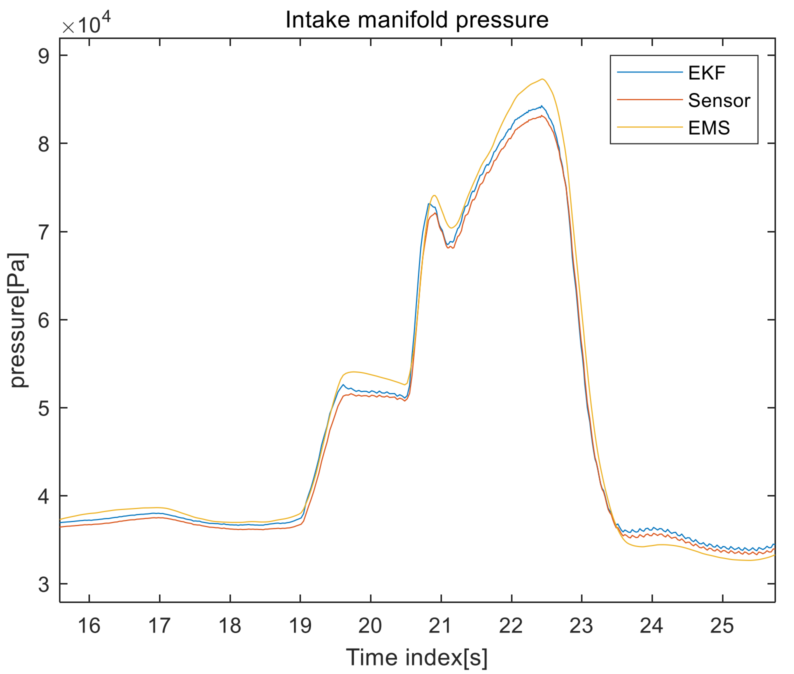

**Figure 9 Estimated intake manifold pressure of centralized EKF (2)**

Intake valve air mass flow rate can be calculated using volumetric efficiency and intake manifold pressure. Figure 10, 11 shows that air mass flow rate using centralized EKF estimated intake manifold pressure and pressure sensor value, pressure value from EMS.

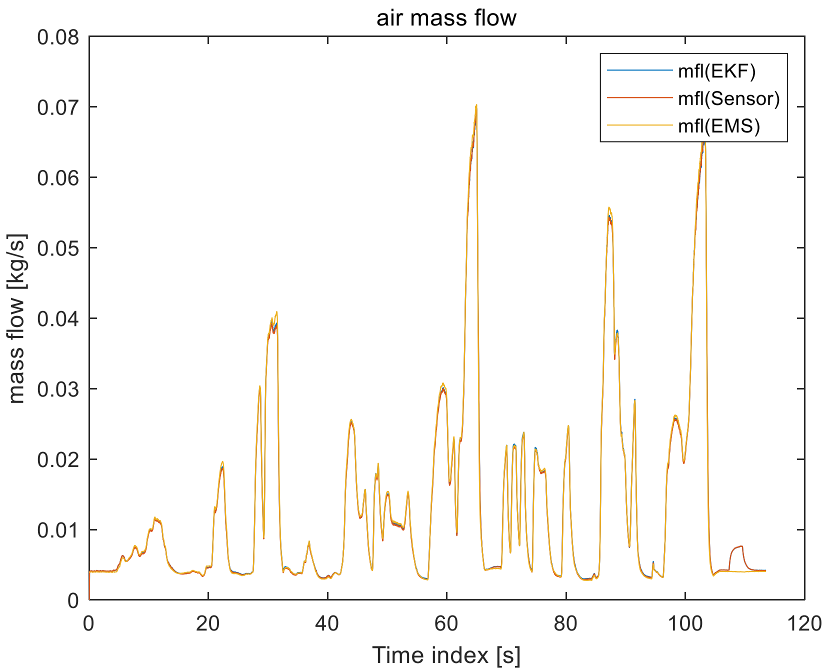


**Figure 10 Estimated intake valve air mass flow rate of centralized EKF (1)**

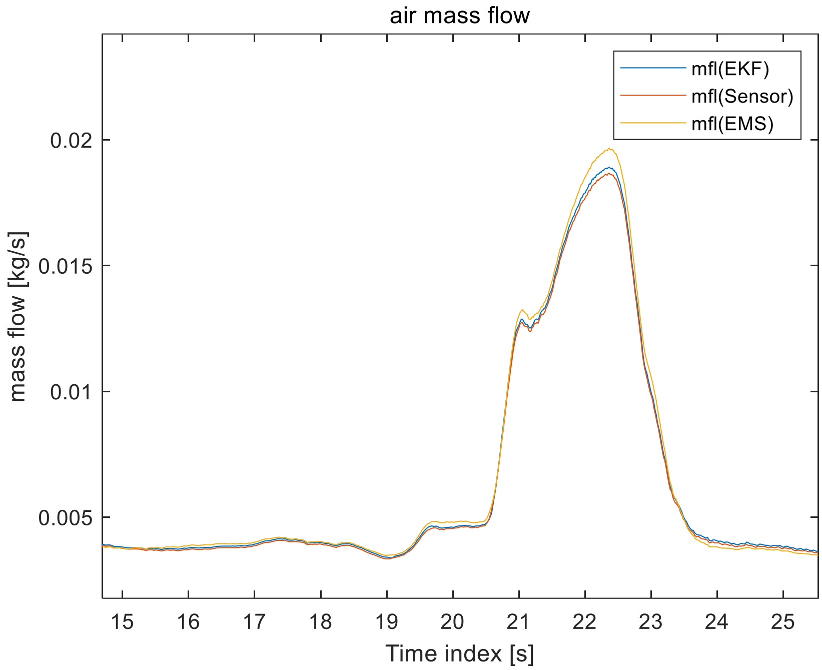


**Figure 11 Estimated intake valve air mass flow rate of centralized EKF (2)**

Simulation result shows that centralized EKF estimated pressure and mass flow rate values are between sensor value and EMS value. This result is reasonable because EKF uses prediction based on system dynamics and update based on sensor value.

One effective method to evaluate the accuracy is comparing Root Mean Square Error (RMSE). RMSE can be derived by following equation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(x_k - \hat{x}_k)^2}$$

Since true value $x_k$ is not known, it is assumed that EMS value is true value. Based on this assumption, RMSE can be calculated and are shown in Table 1.

| | Intake manifold pressure (EKF) [Pa] | Intake manifold pressure (Sensor) [Pa] | Air mass flow rate of intake valve (EKF) [kg/s] | Air mass flow rate of intake valve (Sensor) [kg/s] |
|---|---|---|---|---|
| RMSE | $3.2733 \cdot 10^{3}$ | $3.2080 \cdot 10^{3}$ | $7.5612 \cdot 10^{-4}$ | $8.3043 \cdot 10^{-4}$ |

**Table 1 RMSE of centralized EKF based on EMS value.**

Result shows that RMSE of air mass flow rate of intake valve by centralized EKF estimation is smaller than RMSE of Sensor. It means that centralized EKF estimated mass flow rate is between EMS and sensor value, which is same result of Figure 10-11.

## 4.2. Decentralized Extended Kalman Filter

All used data for simulation of decentralized EKF is same as centralized EKF. Simulation result of decentralized EKF estimated intake manifold pressure is shown in Figure 12, 13 with pressure sensor value, pressure value from EMS.

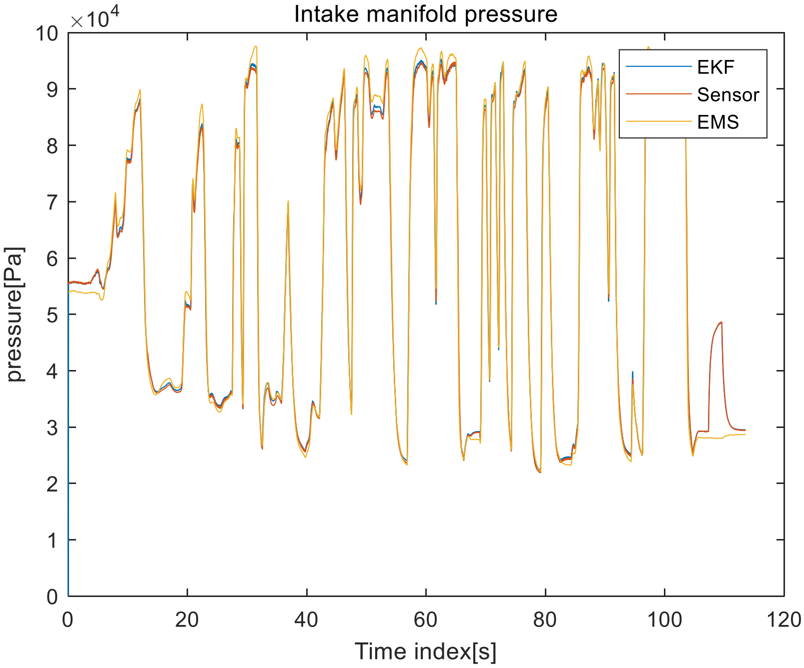


**Figure 12 Estimated intake manifold pressure of decentralized EKF (1)**

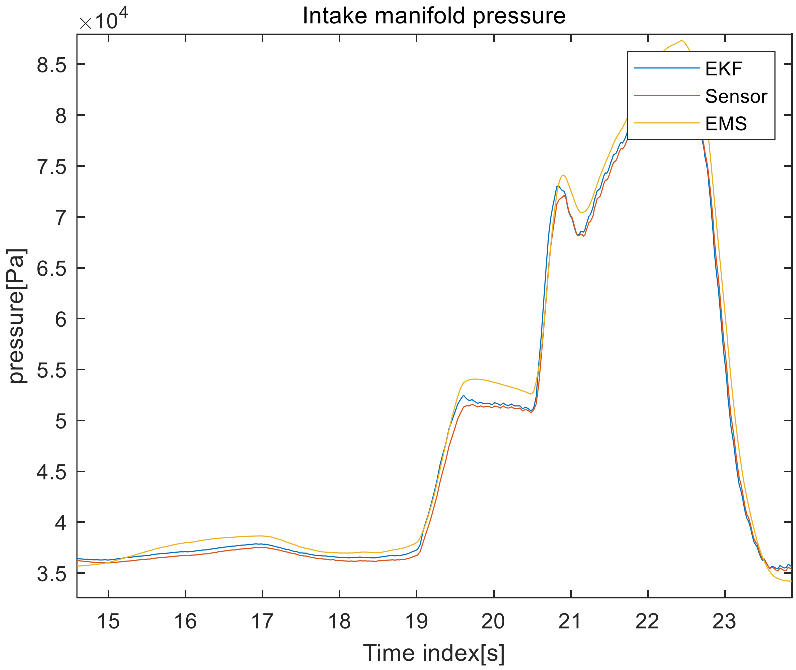


**Figure 13 Estimated intake manifold pressure of decentralized EKF (2)**

Intake valve air flow can be calculated using volumetric efficiency and intake manifold pressure. Figure 14, 15 show that air mass flow rate using decentralized EKF estimated intake manifold pressure and pressure sensor value, pressure value from EMS.

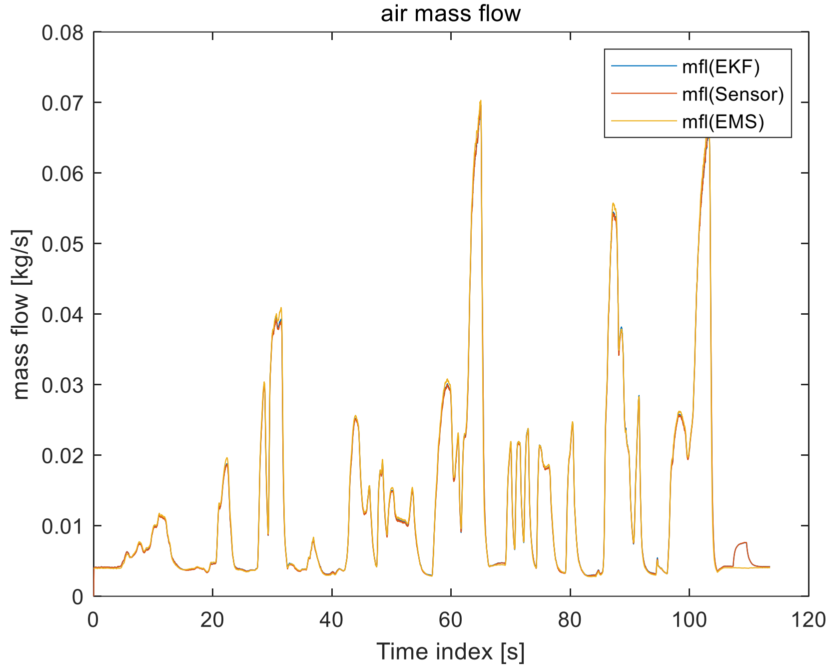


**Figure 14 Estimated intake valve air mass flow rate of decentralized EKF (1)**

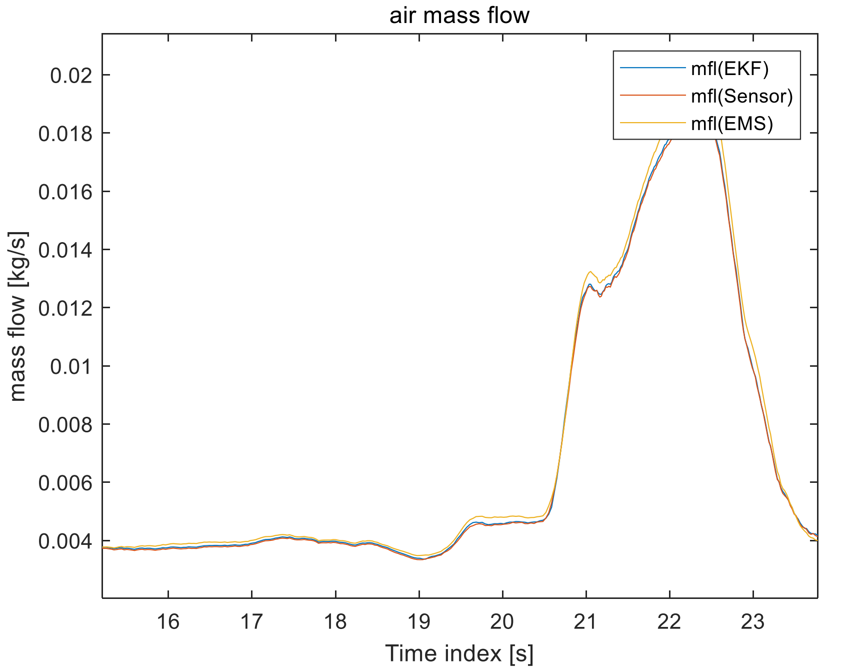

**Figure 15 Estimated intake valve air mass flow rate of decentralized EKF (2)**

Simulation result shows that decentralized EKF estimated pressure and mass flow rate values are between sensor value and EMS value.

Using same assumption of centralized EKF estimation that EMS value is true value, RMSEs can be calculated and are shown in Table 2.

| | Intake manifold pressure (EKF) [Pa] | Intake manifold pressure (Sensor) [Pa] | Air mass flow rate of intake valve (EKF) [kg/s] | Air mass flow rate of intake valve (Sensor) [kg/s] |
|---|---|---|---|---|
| RMSE | $3.3118 \cdot 10^{3}$ | $3.2080 \cdot 10^{3}$ | $7.5829 \cdot 10^{-4}$ | $8.3043 \cdot 10^{-4}$ |

**Table 2 RMSE of decentralized EKF based on EMS value**

Result shows that RMSE of air mass flow rate of intake valve by decentralized EKF estimation is smaller than RMSE of Sensor. It means that decentralized EKF estimated mass flow rate is between EMS and sensor value, which is same result of Figure 14-15.

# Chapter 5

# Conclusion

In this paper dynamic models of throttle flow, EGR flow, intake valve flow, pumping fluctuation, and first order delayed sensor model are established. With these dynamic models and two different types of sensor, centralized and decentralized EKF can be established. Using these two types of EKF, we can simulate estimation of intake manifold pressure and intake valve air mass flow. At last RMSE of each EKF is calculated to derive accuracy of EKF.

Since EMS values are not true values, RMSE has limit that it cannot guarantee the actual accuracy. In order to validate the accuracy, same algorithm of this paper needs to be implemented in EMS software and observe the behavior of oxygen sensor whether lambda peaks

One more caution to be considered that calculation time is not considered in this paper. Since time step of discretization is assumed to $\Delta t = \frac{180}{6N}$, one loop of EKF calculation needs be shorter than this time. Under assumption that engine has limit of 6000 RPM, one loop calculation should be shorter than 5ms. Since calculation time varies depending on performance of hardware, it also needed to be validated with real ECU.

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# 초 록

# 확장칼만필터를 이용한 EGR이 적용된 가솔린 엔진의 공기 흡입량 예측

가솔린 내연기관 자동차의 유해 배출가스를 줄이기 위해서는 삼원촉매의 역할이 가장 중요하다. 이러한 삼원촉매는 그 효율이 연료와 공기의 혼합비율이 화학량론적 수인 14.7 부근에서 그 효율이 가장 높기 때문에 이를 14.7 부근에서 제어하는 것이 배출가스를 줄이는데 중요한 역할을 한다. 연료와 공기의 비율을 14.7 부근에서 제어하기 위해서는 흡기 밸브로 흡입되는 공기량을 정확하게 추정해야 하는데, 흡기 밸브로 유입되는 공기량은 흡기 매니폴드 내부의 압력과 체적 효율을 통해 구할 수 있다. 체적 효율은 별도의 시험을 통해 미리 구할 수 있기 때문에, 흡기 매니폴드 내부의 압력을 추정하면 흡기 밸브로 유입되는 공기량을 계산할 수 있다. 흡기 매니폴드 내부의 압력센서가 있음에도 이 값을 그대로 사용하지 못하는 이유는 센서 자체의 딜레이가 있기 때문에 급격하게 압력이 변하는 구간에서는 센서 값을 신뢰할 수 없기 때문이다. 따라서 흡기 매니폴드 내부의 압력은 추정값을 사용하는 것이 더 정확하다.

본 연구에서는 확장칼만필터를 사용하여 흡기 매니폴드 내부의

압력과 이를 통한 흡기 밸브로 유입되는 공기량을 추정한다. 확장칼만필터 모델 예측을 위해서 쓰로틀을 통해 유입되는 공기량, EGR을 통해 유입되는 공기량, 흡기 밸브로 유입되는 공기량, 펌핑 변동에 의한 압력 변화를 수학적으로 모델링한다. 확장칼만필터 관측기 업데이트를 위해서는 흡기 매니폴드 내부의 압력센서와 쓰로틀 전단에 위치한 흡입공기량 센서를 사용한다. 또한 서로 다른 종류의 두가지 센서를 사용하여 추정하기 때문에 이를 중앙 집중형 확장칼만필터와 분산형 확장칼만필터로 다르게 구현하여 그 결과값을 비교한다. 결과값 비교에는 엔진제어시스템에서 사용하는 값을 참값이라고 가정하여, 평균 제곱근 오차를 사용한다.

**주요어 :** 가솔린 엔진, 흡기 매니폴드 압력, 흡입 공기량 추정, 확장칼만필터

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